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AUTOMATED CAST QUALITY INSPECTION USING DEEP LEARNING

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ABSTRACT

Casting is a manufacturing process that produces the desired final product. These casting components are required to have high dimensional and geometrical accuracies. Thus, there is a need to inspect and detect the defects in the cast product. The quality inspection methods have been developing in various ways, and one of them is through Image Processing, Computer Vision and Deep Learning. As this is a repetitive task, human intervention can be eliminated and make our purpose automated. In this project, we collected the data of the cast component (Pump impellor) and did imagery analysis. Detection is primarily a binary classification problem where the Convolutional Neural Network model predicts whether the cast component is defective or not. If the cast component is a defected one, then the Multi-classifier CNN model predicts the type of defect that the cast component possesses. A specialized arm mechanism separates the defective cast component from the production line. The data relating to each component gets entered into the logbook automatically. The production house gets alerted based on the data in the logbook. Implementation of this technology will significantly improve productivity and reduce the human force for visual inspection.

KEYWORDS: Cast Quality, Image Processing, Computer Vision, Deep Learning, Convolutional Neural Network (CNN), Binary Classification, Multi-Classification & Inspection

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Original Article

1. INTRODUCTION

Manufacturing industries consider the casting process as an initial step that results in the best outcome of the product. Casting is a manufacturing process that can create duplicates or replicas of a specified component with a complicated shape. This process should undergo a critical quality check to reduce the defects in the casting samples. So, quality management has its importance in the manufacturing sector. Every manufacturing industry has a Quality Inspection department to maintain the quality checks of the casting samples. Usually, this quality inspection happens with human intervention, and some industries do a manual inspection.

Though there are many ways of quality inspection for the casting process as a passage of high-frequency waves and liquid penetration in non-destructive testing, the involvement of humans can cause inaccuracies in the identification of defects. Humans have a scope of making mistakes that leads to the possibility for misinterpretation of flaws.

As technology is tremendously changing the traditional trends, the quality management for casting emerged in various ways. Riaz, F., et al [1] proposed an innovative approach for detecting casting defects using the image segmentation process. Their proposed system uses the KMeans clustering technique to identify the surface defects like blowholes, pinholes, and cracks. They have collected images of casting samples with defects. They have used the Gaussian filtering preprocessing technique to reduce the noisy data. Now the KMeans clustering

algorithm can identify the defects in the input casting sample image. They proposed this inspection process to automate the defect detection process at the production level.

Quality is an essential aspect of the manufacturing process. However, the manufacturing industries have quality control checks in their ways. Ferguson, M., et al [2] framed a defect detection system that identifies the defects and carries out the defective instance segmentation. They have used the Convolutional Neural Network model resulted in a good accuracy for both defect detection and segmentation. The model identifies the casting defects in X-Ray images. They have used Transfer Learning to leverage the prediction accuracy of the trained model.

Image processing techniques paved a path for the automation of quality checks of casting samples. A. Kamalakannan et al [3] figured out an automatic defect detection system using X-ray images of casting components. They have adapted a spatial smoothening of X-ray images which is a grayscale morphological variation. This automatic flaw detection system identifies the defects and classifies the internal defects like blowholes, shrinkages, etc.

Neural Networks are used for computational models to get accurate results. It suits well for image data when it involves predictions in an image or video input. Shraban Kumar Singha et al [4] implemented the concept of Artificial Neural Networks (ANN) to have an analysis and optimization of sand-casting defects. They have considered some parameters like moisture content, permeability, pouring temperature, Green compressive strength, etc., and generated the data. This generated data was trained using the ANN toolbox in the MATLAB environment. The model was able to predict the defects as Expansion effect, Gas effect, and Weak sand effects.

On referring to the previous results and their studies, we have adopted new technologies to make our system more industrial friendly. Unlike machine learning algorithms, we have taken a deep learning approach for defect detection and classification. This automatic detection system improves the quality of the production line. Our proposed model stores all the information of each casting component. When the defective component is addressed with its defect, the quality inspection department gets an alert with the component details to check it out.

2. PROPOSED METHODOLOGY

Our proposed methodology involves both detection and identification of the defects in the casting components. Moreover, the system also maintains a logbook that contains the details of all the casting components. The model consists of the conveyor belt where the casting components move on it and a specialized arm to separate the defective component from the normal flow. We have used deep learning to make automatic detection of surface defects.

As deep learning needs a large dataset to train the model, we have taken the cast component images from the Kaggle repository [10]. This dataset comprises both defective and non-defective images of the casting component. There are 3758 images of defective cast components and 2875 images of non-defective cast components. The shape of each image is 300*300. The defective set has all types of defects that occur during the casting process of the submersible pump impeller. After imagery analysis and pre-processing those images, we have trained the Convolutional Neural Network (CNN) model with image data and their respective labels to perform binary classification. This model has an input layer, seven hidden layers, and an output layer. This model differentiates the good cast product from the defective ones.

As inspection is carried out at the production line, we capture the image of the cast component on the conveyor belt. This image gets converted into grayscale. The pre-processed image is sent into the CNN binary classifier as the test

data. As this is a binary classification model, the output says whether the component is defective or not. Based on the result, the Arduino UNO micro-controller receives the appropriate decision. If the casting component is predicted defective, the microcontroller activates the rack and pinion mechanism (specialized arm mechanism) to separate them from the normal flow. The image of the defective one is sent into the CNN multi-classifier. We have prepared the defective cast images dataset with common casting defects like Blow shots (1129 images), Cracks (1081 images), and Flash (1167 images). These images are used to train the CNN multi-classification model. This model has an input layer, five hidden layers, and an output layer. This model predicts the type of cast defect. If the casting component is predicted non-defective, the component moves along the conveyor belt, leaving a way to the next component. This process runs very smoothly without any intervention and doesn't cause any stoppage of the motion of the conveyor belt unless instructed by the operator.

In many industries, the components are assigned with component identity numbers to record the details of every cast product for further analysis. Thus, upon detection, we store the data of every component in the Microsoft Excel Sheet automatically. We have used the Data Frame of Pandas library in the Python programming language for excel sheet entry. The referred data includes the Component ID, Status that tells about the defect, and the corresponding image file directory. If many samples lie under the same type of defect, then the production house is alerted with a siren. This automatic process using machine learning benefits the industry with low cost and good accuracy. Figure 1 depicts the workflow of our proposed system.

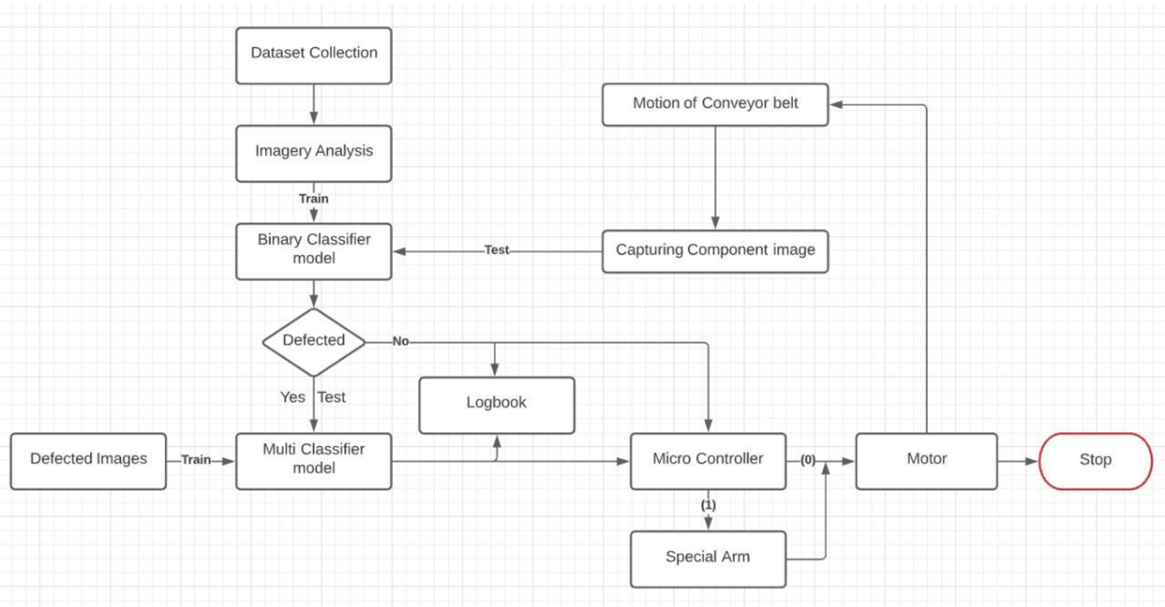

Figure 1: Flowchart of the Proposed System.

We can further improve this model by arranging a closed box with sufficient light while capturing the casting images, by using an x-ray scanner that can capture images in all six degrees of freedom for better predictions.

3. RESULTS

The successful implementation of our proposed system results in detecting defective cast components and identifying the defect in a defective one. The first outcome of the model is to identify the defective cast component. We have considered a Binary Classification model to predict whether the component is defective or not. Upon feeding the CNN binary classifier

with the training and testing data for training and evaluating, we have achieved 99.16% of test accuracy as shown in figure 2.

Figure 2: Binary Classification Model Evaluation.

Table 1 is the classification report that has different evaluation metrics considered to verify the performance of the model we built.

Table 1: Evaluation Metrics

	precision	recall	f1-score	support
0	1.00	1.00	1.00	453
1	0.99	1.00	0.99	262
accuracy			1.00	715
macro avg	1.00	1.00	1.00	715
weighted avg	1.00	1.00	1.00	715

Here ‘0’ refers to the defected one, while ‘1’ refers to the non-defected one. From the above table, it is clear that the model we have, can predict the image of the cast component accurately.

The second outcome of our model is to identify the defect in a defective component. We have used a Multi classification model to identify the defect. The model has attained 95.08% of accuracy as shown in figure 3.

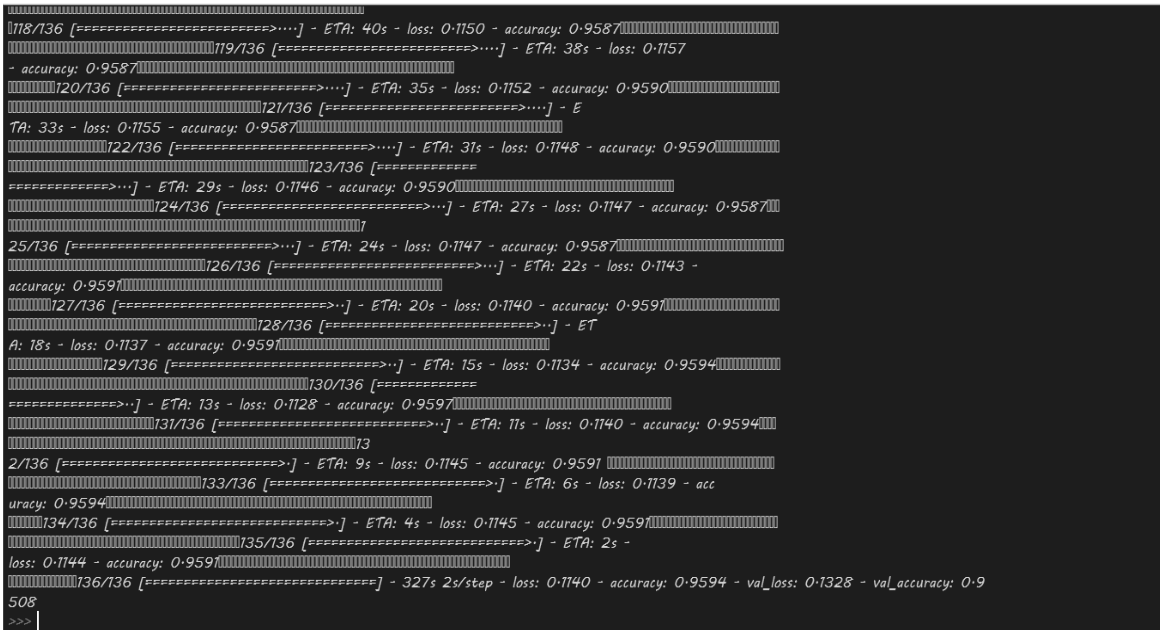

Figure 3: Multi-Classification Model Evaluation.

As we have considered the three common surface defects of the casting component, the model identifies the defect in the defective cast component. Figure 4 depicts the defective cast component having the defect like the bubble-shaped cavities. These cavities are considered as Blow Shots defect in the casting process.

Figure 4: Blow Shots.

Cracks are the most common defect in the casting components. These kinds of cracks are identified on the surface of the cast component by the model as shown in figure 5.

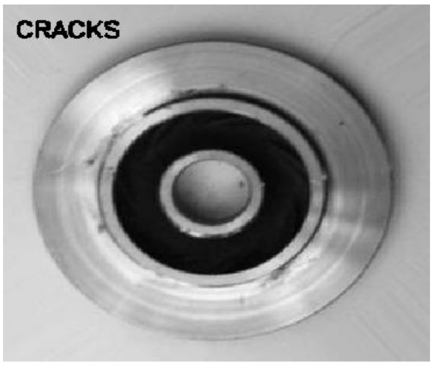

Figure 5: Cracks.

Our model identifies the defective component with excess material on the edges as a Flash defect. These components have poor geometric accuracies. The cast components with the flash defect are considered as defected as shown in figure 6.

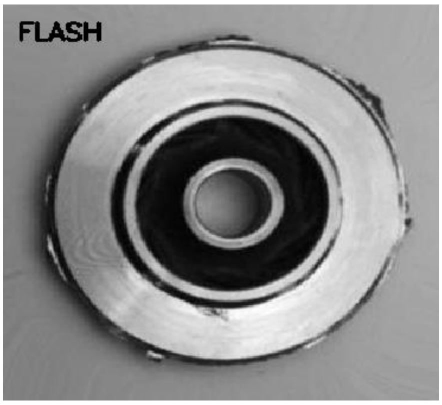

Figure 6: Flash.

As the component passes through the conveyor belt, we capture the image of that component and pass that as our test data to the binary classification model to predict. The output of the model is sent to the Arduino UNO micro-controller to perform its duty. If the image is predicted as a defective one, then the micro-controller activates the rack and pinion mechanism. This arm moves the component across the conveyor belt and thus the component is gets separated from the actual flow of the components. If the component is predicted as a fair one with no defects, then the motor rotates allowing the next component to undergo inspection.

The working prototype on how the system works is depicted below, where the testing cast image for inspection is provided as a static input. When we pass the image of defected cast impeller, the roller of the conveyor belt rotates and the special arm mechanism gets activated as shown in figure 7.

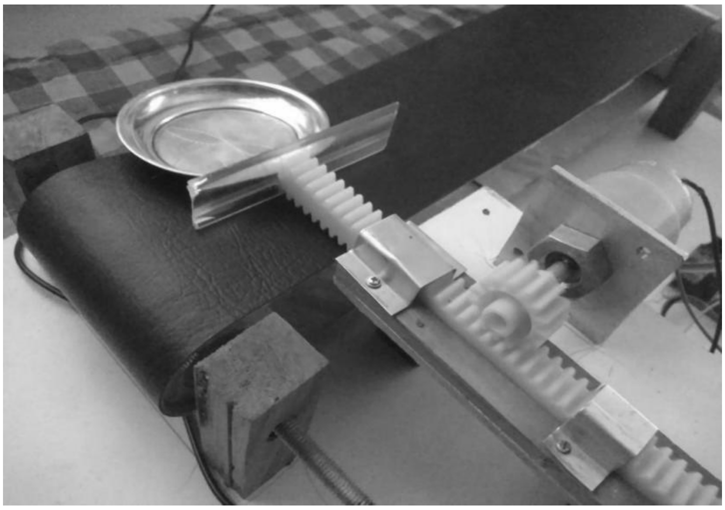

Figure 7: Special Arm Mechanism when Cast is Defective.

When we pass the image of non-defected cast impeller, the roller of the conveyor belt rotates such that it allows another one as shown in figure 8.

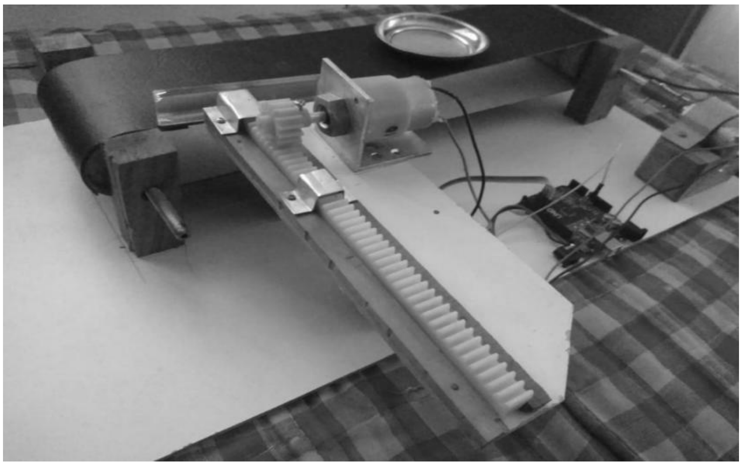

Figure 8: Special Arm Mechanism when Cast is not Defective.

We need to store the data of every component in the logbook. We have taken 100 sample images that were not a part of the training set of the model. After prediction, the data gets entered into Microsoft Excel Sheet automatically, and the sheet gets updated upon new entries, which is as shown below in figure 9.

	A	B	C
1	**Component_ID**	**Condition**	**Image**
2	Cast_1	Flash	C:/Users/Karthik/Desktop/Project/Logbook Data/1.jpeg
3	Cast_10	Non-defected	C:/Users/Karthik/Desktop/Project/Logbook Data/10.jpeg
4	Cast_100	Flash	C:/Users/Karthik/Desktop/Project/Logbook Data/100.jpeg
5	Cast_11	Flash	C:/Users/Karthik/Desktop/Project/Logbook Data/11.jpeg
6	Cast_12	Blow Shots	C:/Users/Karthik/Desktop/Project/Logbook Data/12.jpeg
7	Cast_13	Flash	C:/Users/Karthik/Desktop/Project/Logbook Data/13.jpeg
8	Cast_14	Cracks	C:/Users/Karthik/Desktop/Project/Logbook Data/14.jpeg
9	Cast_15	Blow Shots	C:/Users/Karthik/Desktop/Project/Logbook Data/15.jpeg
10	Cast_16	Flash	C:/Users/Karthik/Desktop/Project/Logbook Data/16.jpeg
11	Cast_17	Flash	C:/Users/Karthik/Desktop/Project/Logbook Data/17.jpeg
12	Cast_18	Flash	C:/Users/Karthik/Desktop/Project/Logbook Data/18.jpeg
13	Cast_19	Cracks	C:/Users/Karthik/Desktop/Project/Logbook Data/19.jpeg
14	Cast_2	Non-defected	C:/Users/Karthik/Desktop/Project/Logbook Data/2.jpeg

Figure 9: Logbook.

4. CONCLUSIONS

For removing the defective product, the inspection process is to be carried out manually. All industries have their quality inspection departments especially. The idea of automating the process of inspection of cast products has been undertaken. The response of which, inspection time is reduced without compromising the level of accuracy. From this, we can eliminate the human-made mistakes that have a chance to miss any of the defects. This solution reduces the cost of production if there any flaw in the manufacturing process. The electronic controller controls the conveyor belt and specialized arm smoothly. This mechanism works on a simple principle, and there is no much complexity involved in the control flow. Above all, this solution provides a high degree of predictability of the cast product quality.

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